Nonholonomic Object Tracking with Optical Sensors and Object Recognition Feedback

Ralph E. Goddard and Fred Hadaegh
The Jet Propulsion Laboratory

ABSTRACT

Robotic controllers frequently operate under constraints. Often, the constraints are imperfectly or completely unknown. In this paper, the Lagrangian dynamics of a planar robot arm are expressed as a function of a globally unknown constraint. Optical sensors are utilized to produce estimates of local constraints. These sensors guide the end effecter over the unknown object. This learning phase generates noisy joint position encoders and tachometers data. A extended continuous-discrete Kalman filter based estimator processes the measurements to compute an estimate of the parametrized object. The output of the estimator is input to a suboptimal combiner. The gradient of the estimated parameter vector is utilized to compute the constraint matrix. During the learning phase, the combiner computes a weighted combination of estimated and measured constraints. The controller uses the constraint estimate to guide the robot arm. Thus a feedback loop is closed around the constraints. As the statistics of the estimated constraint matrix become favorable compared to the stationary statistics of the sensors, the learned constraints gradually reduce the weight of the sensory data.

INTRODUCTION

Robotic tasks in a space environment can benefit from autonomous capability, For example, a sensor placed on the Space Shuttle robot arm could help guide the arm to grapple and secure satellites on retieval missions. For the expected Space Station, robotic manipulators capable of moving in a complex environment with only high level operator supervision are of obvious interest. In the future space environments we envision, it is undesirable that the manipulators contact accidently with other objects. The implications are obvious if, for example, a satellite brought in for repair were to bump the Space Station because of an operator error. The capability to operate autonomously in a space environment is thus a general problem.

In this paper, we formulate the problem in a general context that is useful in many applications. The problem considered is that of motion of a manipulator about an unknown object without a global model of the constraints imposed by the unknown object. A global constraint model implies complete knowledge of the object shape. Without a global model, the constraints are nonholonomic. Nonholomic constraints are locally sensed, in this paper, by placing a sensor on the manipulator end effecter. The sensor data provides information to move the manipulator instantaneously, or locally, while satisfying the sensed constraints, The sensor in this paper is optical. Thus, once the end effecter of the manipulator is placed in proximity to an unknown object by the operator, the controller is able to navigate about the object autonomously. This phase of autonomous movement is denoted the learning phase. In the learning phase, sensed data from the optical sensor, the joint position encoders, and tachometers are processed in an estimator which begins to estimate the unknown object's shape. The estimator is helped greatly because we parametrize the object. In the simulation to follow, we let the object be one of a class of generalized quadratics. Future work will be directed towards removing this assumption. As the, statistics of the estimated object become more favorable compared to the stationary statistics of the optical sensor, the controller weights more heavily the estimated object compared to the optical sensor.

OPEN LOOP DYNAMICS AND CONTROLLER DESIGN

Object Induced Constraints

In general, object constraints are characterized by a set of holonomic hypersurfaces constraining the 6 dimensional Euclidean coordinate space of the end effecter. Let an end effecter with k degrees of freedom, k <= 6, be described by a position vector r; and let r be constrained by m real-valued hypersurfaces:

$$p_i(r)=0; \quad i=1,2 \ \ldots, m \ ; \quad m < k; \ p_i : R^k \rightarrow R^1 \tag{1}$$

It is assumed the hypersurfaces are twice differentiable with respect to r over any joint trajectory of interest. Then from Mason [1]:

$$\frac{\partial p}{\partial r} \dot{r} = 0; \ p^t = [p_1, \cdots, p_m] \tag{2}$$

where an overdot is the time derivative and the superscript t is the transpose. Let C^o be a real-valued matrix representing the sensed nonholonomic constraint such that:

$$C^o \dot{r} = 0; \qquad C^o \in R^{m \times k} \tag{3}$$

Holonomic constraints have been previously described by Mason. The holonomic constraints are globally known for a particular object, Many nonholomonic constraints, on the other hand, constrain only the local motion of the joint trajectory and not the joint coordinates. Therefore, for an unknown object, C^o must be sensed locally on the object. The approach here is to utilize optical sensors on on the end effecter to sense the instantaneous constraints.

Joint Coordinates, Constraints, and Nominal Trajectories

A manipulator with n degrees of freedom is described by a joint vector q of dimension n. Assume the joint angles are subject to constraints, Let there exist a function f expressing the effecter position in terms of joint coordinates and let f be twice differentiable with respect to q. Define the following joint constraint matrix via the system Jacobian:

$$\dot{r} = \frac{\partial f}{\partial q}\,\dot{q} = C^q\,\dot{q} \tag{4}$$

Although the analytical form of the Jacobian is known for a particular manipulator, the sensed constraints Eq. (3) are not *a priori* known, The composite constraint matrix is defined from Eq. (3) and (4):

$$C^o\,\dot{r} = C^o\,C^q\,\dot{q} = C\,\dot{q} = 0 \tag{5}$$

It is obvious that only (n - m) of the joint velocities are independent. Denote by a transformation matrix Q the independent subspace and let a superscript d indicate the nominal (stead y state) trajectory:

$$Q\,\dot{q}^d = \begin{bmatrix} \dot{q}^d_{n-m} \\ \hline \dot{q}^d_m \end{bmatrix}; \quad C\,Q^{-1} = [C_{n-m} \mid C_m]; \tag{6}$$

where subscripts denote dimension. Solving Eq. (5) using the definitions in Eq. (6) yields:

$$‘\ d\ ,\ Q\ ,\ [*]\quad \dot{q}^d_{n-m} \tag{7}$$

where I is the identity matrix of appropriate dimension. The nominal acceleration vector is obtained by differentiating Eq (7).

Joint Commands

A hybrid joint command will be derived as a function of the nominal trajectory. The Lagrangian dynamics of mechanical manipulators is well known from a variety of papers [2]. The formulation here will be *in the* most general context. Therefore, contact forces will be included in the dynamics. For the subsequent simulation, desired contact forces are set to zero indicating that the object is not physically contacted. The dynamics, assuming a stable controller, on the nominal trajectory are:

$$M(q)\,\ddot{q}^d + h(q,\dot{q}^d) + g(q) = u^d + C^t\,\gamma^d\ ; \qquad u^d = u^d_f\ i\text{-}\ u^d_v; \qquad u^d_f = C^t\,\gamma^d \tag{8}$$

where M is the inertial matrix, h is the Coriolis vector, g is the gravity moment, and the control input is composed of a velocity term and a desired force term (γ^d). Expansion of the dynamics about the nominal trajectory yields the error system from which state feedback is computed to stabilize the motion:

$$\Delta\ddot{q} = A\,\Delta\,\dot{q} + B\,\Delta\,u \tag{9}$$

A block diagram of the controller of Figure 1. shows the servo loops about the constraints.

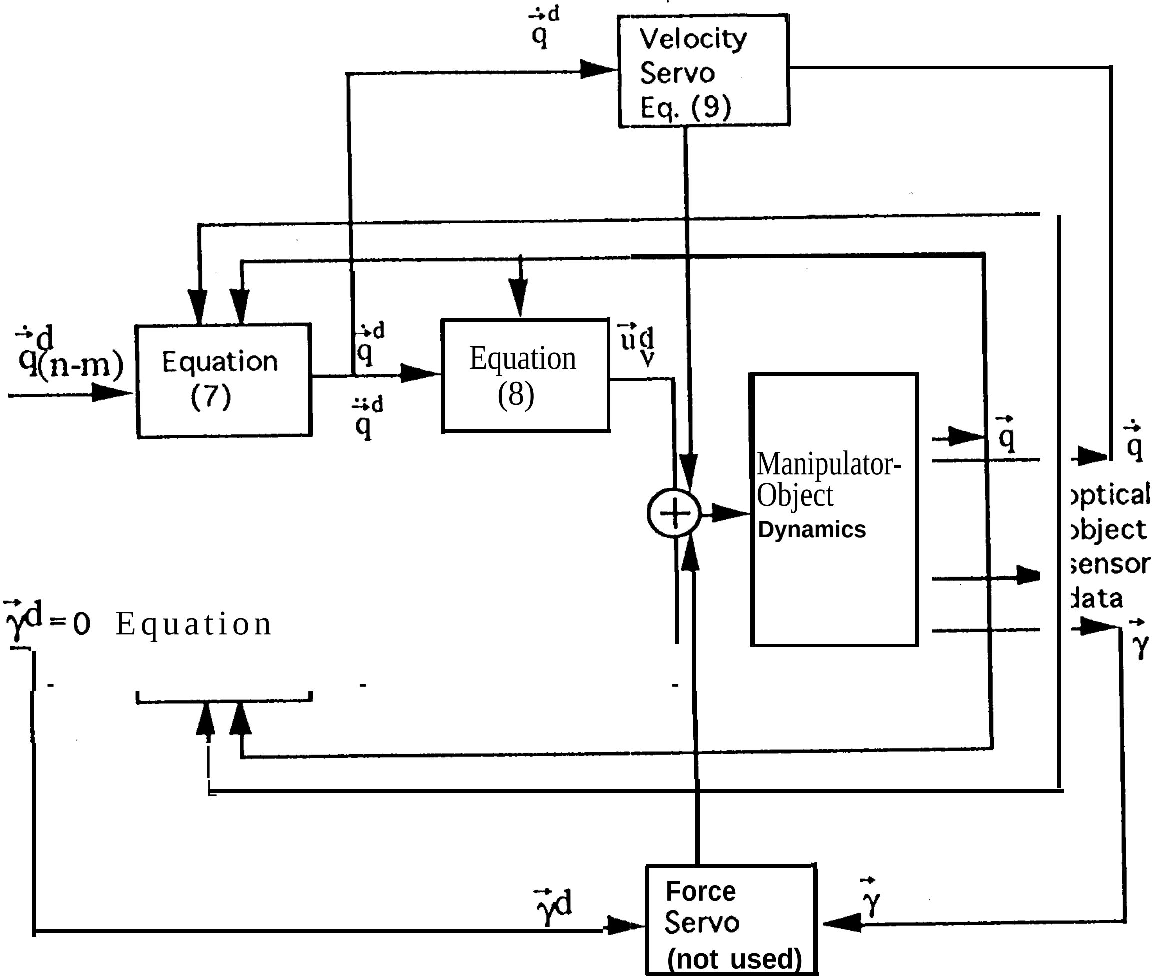


Figure 1. Nominal Controller with Velocity Servo and Zero Desired Contact Forces (γ^d)

OBJECT ESTIMATION

Object Estimator

The goal of the controller design is to "learn" the object. The problem is made specific by assuming that the object is a member of a class of objects. Consider the class of generalized planar quadratics parametrized by 5 coordinates $P = [p_1, \cdots, p_5]$. The constraint matrix in Eq. (5) is defined by requiring the end effecter to maintain an attitude that is normal to the object (to obtain accurate ranging data) while moving tangentially along the object at a constant velocity (so that the object can be 'learned'). Define the object pararneterization to be a state. This make obvious the coupling between the state and the parameter vectors. The state vector and the object "dynamics" are:

$$x^t = [q, \dot{q}]\,; \qquad \dot{p} = 0;\; p(0) = p_0 \tag{10}$$

Therefore the object estimation problem is reduced to estimating an unknown constant vector. The value of the initial object estimate is set from the *a priori* knowledge of the object. The adjoined manipulator/object state vector is $x^t = [q, \dot{q}, p]$. The extended Kalman filter, evaluated on the nominal motion, time propagation in the absence of measurements is:

$$\dot{P} = A(\hat{x})P + P A(\hat{x}) + G V G^t \qquad (11)$$

where V is the spectral density of the actuator noise. The measurement update is:

$$K = P^-(t_k) H^t [H P^-(t_k) H^t + R]^{-1}; \; P(t_k) = [I - KH]P^-(t_k); \; \hat{x} = \hat{x}_k^- + K[z_k - H\hat{x}_k^-] \qquad (12)$$

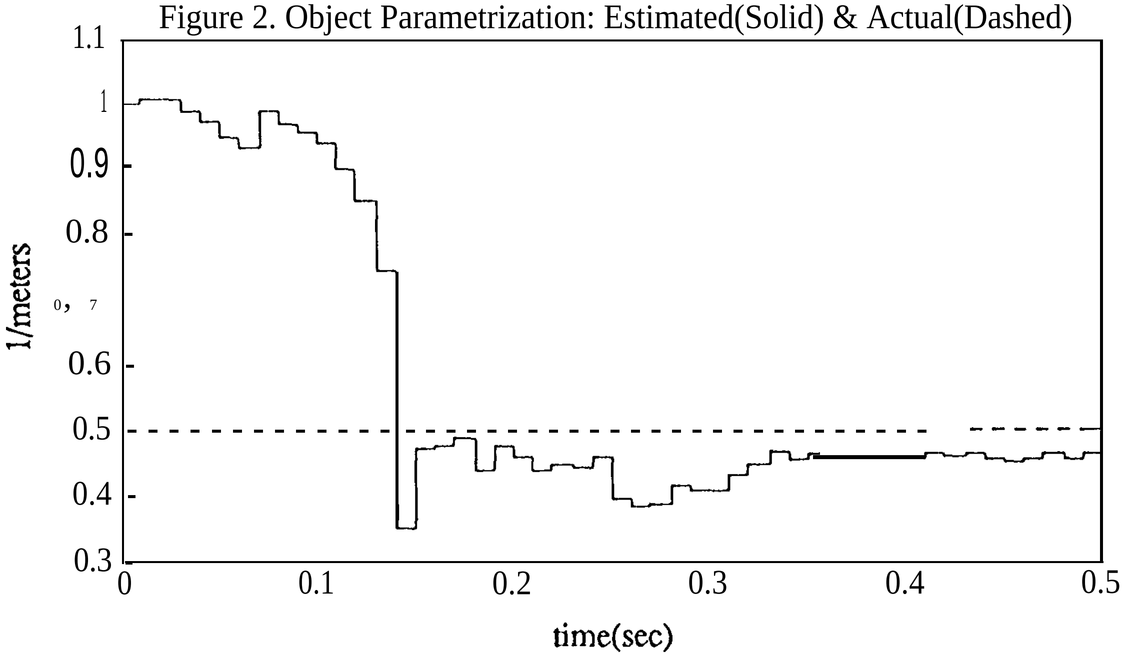
Measurements h consists of joint angles, joint velocities, and object normal vector, in end effecter coordinates. The measurement covariance is R. Then

$$H = \frac{\partial h}{\partial x} \text{ and } A = \frac{\partial \dot{x}}{\partial x} \qquad (13)$$

Simulation

The object constraint data is sensed optically with a trio of ranging sensors providing three contiguous distance measurements. A cubic spline is fit to the 3-tuple range data, from which the local object normal is computed to yield the the constraint matrix. We also model the ranging optics error as uniformly distributed over 10 mm, 3 sigma [4] [5]. One sigma values for angle and tachometer noise are 1 degree and 1 degree/second, respectively. The actuator noise is considered small compared to measurement noise such that V=O is assumed. Eigenvalues of the closed loop error dynamics are set to -10. and the measurement update rate is 10 milliseconds. The simulation results of Figure 2. show the convergence of the object estimate occurs in about 2 time ‘constants, physically indicative of the strong coupling the object has into the manipulator motion.

Figure 2. Object Parametrization: Estimated(Solid) & Actual(Dashed)



CONCLUSION

A generalized controller tracked an unknown generalized quadratic utilizing optics to sense the nonholonomic constraints. A Kalman estimator converged to the object parameterization vector.

ACKNOWLEDGEMENT

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